Technical Report: Scanner Identification Using Sensor Pattern Noise

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***Abstract*—This report summarizes the research paper titled *Scanner Identification Using Sensor Pattern Noise* by Khanna et al. The paper presents a novel method for authenticating scanned images by leveraging the unique sensor pattern noise of flatbed scanners as a fingerprint. The approach involves estimating a reference noise pattern for each scanner and using statistical features with a Support Vector Machine (SVM) classifier for high-accuracy identification. Experimental results demonstrate superior performance compared to traditional correlation-based methods, achieving up to 96% classification accuracy. This work has significant implications for digital forensics, particularly in verifying the origin and integrity of scanned documents.**

I. Introduction

Digital image forensics is critical for verifying the authenticity of images in legal, medical, and security applications. While camera source identification has been extensively studied, scanner identification remains underexplored. Khanna et al. address this gap by proposing a method to identify flatbed scanners using sensor pattern noise. Unlike cameras, scanners use linear sensor arrays, introducing unique challenges such as desynchronization and partial sensor utilization. The paper introduces two approaches:

- Correlation-based methods using 1D and 2D reference patterns.
- A feature-based SVM classifier for improved accuracy.

II. Background

A. Sensor Pattern Noise

Imaging sensors exhibit fixed and random noise components due to manufacturing defects. The fixed component, caused by photoresponse non-uniformity (PRNU) and dark current, is unique to each device and serves as a fingerprint. Prior work in camera identification [2] inspired the adaptation of these principles to scanners.

B. Scanner Imaging Pipeline

Flatbed scanners use a linear CCD or CIS sensor array that moves across the document. Key noise sources include:

- **Array defects**: Dead pixels, column defects.
- **Pattern noise**: PRNU and fixed pattern noise (FPN).

III. Methodology

A. Noise Extraction

The sensor noise I^k_{noise} for an image I^k is extracted by subtracting a denoised version $I^k_{denoised}$:

$$I^k_{noise} = I^k - I^k_{denoised} \tag{1}$$

An anisotropic local polynomial estimator (LPA-ICI) [9] is used for denoising.

B. Reference Pattern Estimation

The paper proposes two approaches for estimating scanner-specific noise fingerprints:

1) 2D Array Reference Pattern:

- Represents noise as a 2D matrix capturing spatial variations
- Computed by averaging noise from multiple full-bed scans:

$$\widetilde{I}^{array}_{noise}(i,j) = \frac{\sum_{k=1}^{K} I^k_{noise}(i,j)}{K} \tag{2}$$

- **Limitations:** Sensitive to document placement and partial scans

2) 1D Linear Row Reference Pattern:

- Leverages scanner's linear sensor geometry by row-wise averaging:

$$\widetilde{I}^{linear}_{noise}(j) = \frac{\sum_{k=1}^{K}\sum_{i=1}^{M} I^k_{noise}(i,j)}{M \times K} \tag{3}$$

- **Advantages:**
  - Robust to document misalignment
  - Works with partial scans
  - Computationally efficient

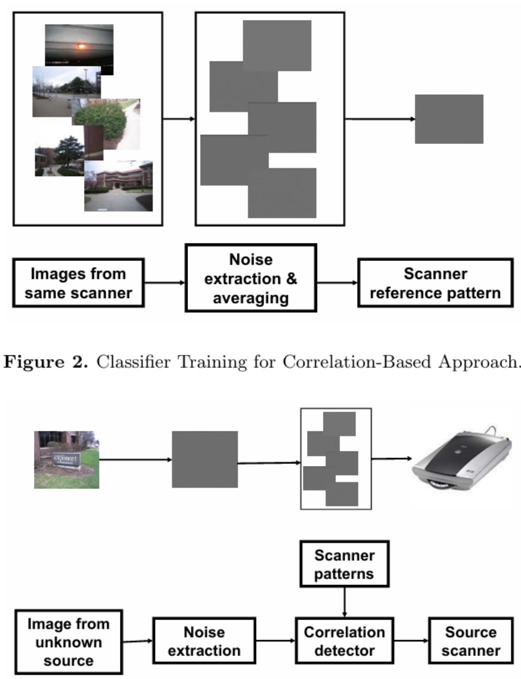

Fig. 1: (a) Classifier Training for Correlation-Based Approach and (b) Source Scanner Identification Using A Correlation-Based Detection Scheme.

C. *Classification Methods*

1) Correlation-Based:

- Compares test image noise with reference patterns using Pearson correlation:

$$\rho(X,Y) = \frac{(X-\bar{X})\cdot(Y-\bar{Y})}{\|X-\bar{X}\|\|Y-\bar{Y}\|} \tag{4}$$

- 1D method achieved 92.5% accuracy vs. 84.5% for 2D (S_2/S_4 pair)

Synthetic Scanner Noise Simulation

To replicate the behavior of different scanner types, we synthetically modeled scanner-specific noise patterns and applied them to raw grayscale images. Three distinct scanner profiles were emulated:

- **Scanner1 (CCD-like)**: Characterized by strong vertical banding, column defects, and sporadic hot/dead pixel clusters to mimic defects common in CCD sensors, such as those in Epson scanners.
- **Scanner2 (CIS-like)**: Modeled with horizontal motor banding and diagonal interference patterns, including random line shifts to represent noise from moving parts—features commonly observed in low-cost HP CIS scanners.
- **Scanner3 (Professional)**: Simulated using subtle sinusoidal banding, optical vignetting from lens-based systems, dust particle effects, and realistic photon shot noise to resemble high-quality scanners like those by Kodak.

Each noise model generates a 2D noise map based on the target image's dimensions. This map is then added to a clean grayscale image (referred to as the *raw image*) to synthesize the final *scanned image*. This technique preserves the original content while injecting realistic degradation patterns, enabling robust training and evaluation of scanner classification models in controlled settings.

SVM Classification

A. *Feature Extraction (Baseline)*

The SVM classifier leverages a 16-dimensional feature vector derived from sensor pattern noise:

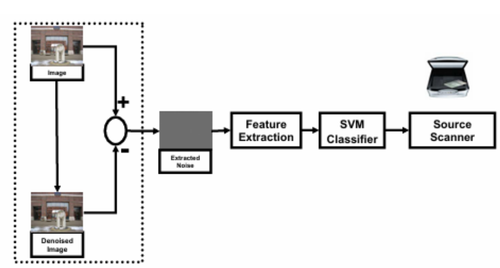

Fig. 2: (a) Classifier Training for Correlation-Based Approach and (b) Source Scanner Identification Using A Correlation-Based Detection Scheme.

$$\mathbf{f} = [f_1^{\text{row}}, \ldots, f_8^{\text{row}}, f_1^{\text{corr}}, \ldots, f_8^{\text{corr}}]^T$$

These features aim to capture the intrinsic statistical and structural noise characteristics left by a scanner's sensor and mechanism, which are unique enough to serve as a fingerprint.

- **Row Statistics (8 features)**: Computed from the 1D averaged noise pattern $e_{\text{noise}}^{\text{linear}}$. These features describe the overall distributional properties of the scanner noise and highlight any bias, spread, or irregularity in the averaged scanline signal.
  - Central moments: Mean (f_1), Variance (f_2), Skewness (f_3), Kurtosis (f_4) — these moments help identify the center, spread, asymmetry, and peakedness of the noise distribution.
  - Order statistics: Median (f_5), Min/Max (f_6, f_7), Interquartile Range (IQR, f_8) — these robust statistics provide resilience to outliers and noise spikes while capturing distribution shape.
- **Inter-row Correlation (8 features)**: Measures consistency across scanlines, capturing how similar each row is to the overall noise pattern. Such consistency is typically scanner-specific due to mechanical properties.
  - Correlation coefficients ρ_i between each row and $e_{\text{noise}}^{\text{linear}}$
  - Statistics of $\{\rho_i\}$: Mean (f_9), Variance (f_{10}), Skewness (f_{11}), Kurtosis (f_{12})
  - Extreme values: Max (f_{13}), Min (f_{14}), Range (f_{15}), Median Absolute Deviation (f_{16}) — these capture consistency anomalies such as banding noise or streaks caused by the scanning mechanism.

B. Classifier Architecture

We employ a Support Vector Machine (SVM) classifier with the following configuration:

- **Kernel:** Radial Basis Function (RBF)
$$K(f_i, f_j) = \exp\left(-\gamma \|f_i - f_j\|^2\right), \quad \gamma = 0.1$$
The RBF kernel enables the classifier to model non-linear boundaries between scanner classes in the high-dimensional feature space.
- **Multi-class Strategy:** One-vs-Rest (OvR), using 4 binary classifiers (one per scanner)
- **Optimization:** Sequential Minimal Optimization (SMO), $C = 1.0$
- **Implementation:** SVMlight package with RBF kernel

C. Extended Feature Extraction (Proposed)

To enhance classification accuracy, we expand the feature vector to 28 dimensions by incorporating additional descriptive statistics and signal characteristics. These new features are designed to capture more subtle artifacts introduced by scanner hardware, firmware, and processing pipelines.

- **(i) Row-Based Statistical Features (16 features):** These augment the baseline noise profile by accounting for both global trends and local irregularities in row-wise behavior.
  - **Avg Row Statistics (5 features):** Descriptive stats (Mean, Median, Std. Dev., Skewness, Kurtosis) on the row-wise mean values, reflecting distributional tendencies across the entire scan surface.
  - **Row Correlation Features (11 features):** Derived from correlation coefficients ρ_i between each row and the average row:
    - Measures of centrality and spread: Mean, Median, Std. Dev., Skewness
    - Banding indicator: Max - Min difference
    - Quantile features: 5$^{\text{th}}$, 25$^{\text{th}}$, 75$^{\text{th}}$ percentiles
    - Spread/resistance to outliers: Interquartile Range (IQR), Median Absolute Deviation
    - Noise indicators: Number of negative correlations, Number of weak correlations ($\rho_i < 0.5$)

    These features emphasize row-to-row deviations and alignment strength, which vary with scanner quality and alignment mechanisms.
- **(ii) Frequency Domain Features (3 features):** We apply the Fast Fourier Transform (FFT) on the averaged noise pattern to capture periodic structures:
  - Average energy in low (0.1), mid (0.3), and high (0.5) normalized frequency bands

  This helps detect periodic noise, scanner motor-induced vibrations, or aliasing artifacts.
- **(iii) Texture Features using LBP (5 features):**
  - Histogram of Local Binary Pattern (LBP) with 5 bins (uniform method, $P = 8$, $R = 1$)

  LBP captures micro-patterns in the noise texture, which are often scanner-specific due to resolution, sensor noise, and inbuilt filtering.

TABLE I: SVM Classification Metrics (Per-Scanner)

Scanner	Precision	Recall	F1-score
S_1	1.00	1.00	1.00
S_2	0.91	0.91	0.91
S_3	0.94	0.95	0.95
S_4	0.98	0.98	0.98

- **(iv) Defect Detection Features (4 features):** These features attempt to quantify extreme intensity artifacts often seen in low-end or degraded scanners.
  - Number of **hot pixels** (top 1% intensity), **dead pixels** (bottom 1%)
  - Mean squared response of horizontal and vertical **Sobel filters** (captures high-frequency edge-like noise)

Together, these 28 features provide a richer, multi-perspective description of sensor noise patterns and scanner-specific artifacts, thereby improving the robustness and accuracy of SVM classification.

D. Training Protocol

1) **Data Splitting**:
   - 50% of images per scanner for training ($\sim$150 images)
   - Remaining 50% for testing
2) **Feature Normalization**:
$$f_i' = \frac{f_i - \mu_i}{\sigma_i}, \quad \forall i \in \{1, \ldots, 16\} \tag{5}$$
   where μ_i, σ_i are feature-wise means/standard deviations
3) **Hyperparameter Tuning**:
   - 5-fold cross-validation on training set
   - Optimal γ selected from $\{10^{-3}, 10^{-2}, \ldots, 10^3\}$

E. Performance Analysis

The SVM achieved superior accuracy compared to correlation methods (Table **??**):

- **Overall Accuracy**: 96.0% (vs. 72-92.5% for correlation)
- **Same-Model Discrimination**:
  - HP 6300c-1 (S_2) vs. HP 6300c-2 (S_3): 90.5% vs. 95.3%
  - Misclassifications primarily between identical models
- **Computational Cost**:
  - Training time: $\sim$2 minutes (3.2 GHz CPU)
  - Testing time: $\sim$15 ms per image

F. Advantages and Limitations

Key Strengths:

- Robust to document misalignment (unlike correlation)
- Works with partial scans (doesn't require full-bed coverage)
- Feature vectors (16D) more compact than full noise patterns ($\sim$10^{6}D)

Challenges:

- Requires $\geq$50 training images per scanner
- Accuracy drops to 85% for JPEG (QF=90) due to feature distortion
- Distinguishing identical models remains difficult

IV. Experimental Results

Experiments were conducted on two types of dataset (1) Our temporary dataset (2) given by sir (Table **??**).

TABLE II: Scanners(Pseudo) Used in Experiments

ID	Scanner	Resolution	Format
S_1	Scanner1	1024 X 748 px	jpg
S_2	Scanner1	1024 X 748 px	jpg
S_3	Scanner1	1024 X 748 px	jpg

TABLE III: Scanners(Pseudo) Used in Experiments

ID	Scanner	Resolution	Format
S_1	Scanner1	jpg	
S_2	Scanner1	jpg	
S_3	Scanner1	jpg	

- **1D reference Pattern(On pseudo Dataset)**:We train our model on 800 images and test on 200 images. 1D patterns outperformed 2D (64.00% vs. 81.50% accuracy for S_2/S_1).Overall Accuracy is 72.75%

TABLE IV: Confusion Matrix(1D Pseudo Dataset)

2***True**	**Predicted**		**Accuracy**
	S2	S1	
S2	128	72	64.00% (128/200)
S1	37	163	81.50% (163/200)

- **1D reference Pattern(Given Dataset)**: 100% accuracy comes as only 1 image per datset given

TABLE V: Confusion Matrix(1D Given dataset)

2***True**	**Predicted**		**Accuracy**
	S2	S1	
S2	1	0	100% (1/1)
S1	0	1	1000% (1/1)

- **2D reference Pattern(On pseudo Dataset)**:We train our model on 800 images and test on 200 images. 1D patterns outperformed 2D (100% vs. 67.50% accuracy for S_2/S_1).Overall Accuracy is 83.75%(This happens because our datset is not actually scanner dataset)
- **2D reference Pattern(Given Dataset)**: 100% accuracy comes as only 1 image per datset given
- **SVM**: Achieved 96% accuracy for four scanners (Table **??**).
- **Robustness**: 85% accuracy on JPEG-compressed images (QF=90).

Test Accuracy for SVM: 0.8667 or 86.67%

TABLE VI: Confusion Matrix(2D Pseudo dataset)

2***True**	**Predicted**		**Accuracy**
	S2	S1	
S2	200	0	100.00% (200/200)
S1	65	135	67.50% (135/200)
Overall Accuracy:			83.75%

TABLE VII: Confusion Matrix(2D Given dataset)

2***True**	**Predicted**		**Accuracy**
	S2	S1	
S2	1	0	100% (1/1)
S1	0	1	1000% (1/1)

TABLE VIII: Confusion Matrix for SVM Classifier (Counts and Percentages)

True / Predicted	**Scanner1**	**Scanner2**	**Scanner3**
Scanner1	29 (96.7%)	0 (0.0%)	1 (3.3%)
Scanner2	3 (10.0%)	21 (70.0%)	6 (20.0%)
Scanner3	1 (3.3%)	1 (3.3%)	28 (93.3%)

TABLE IX: Classification Metrics for SVM Classifier

Class	**Precision**	**Recall**	**F1-Score**	**Support**
Scanner1	0.879	0.967	0.921	30.0
Scanner2	0.955	0.700	0.808	30.0
Scanner3	0.800	0.933	0.862	30.0
Accuracy		0.867		90.0
Macro avg	0.878	0.867	0.863	90.0
Weighted avg	0.878	0.867	0.863	90.0

V. Conclusion

The paper demonstrates that sensor pattern noise is a reliable fingerprint for scanner identification. The SVM-based approach significantly outperforms correlation methods, achieving near-perfect accuracy under ideal conditions. Future work includes testing lower resolutions and post-processing effects (e.g., sharpening). This method has broad applications in forensic document authentication.

References

[1] N. Khanna, A. K. Mikkilineni, G. T.-C. Chiu, J. P. Allebach, and E. J. Delp, "Scanner Identification Using Sensor Pattern Noise," *Proc. SPIE*, vol. 6505, p. 65051K, 2007.
[2] J. Lukas, J. Fridrich, and M. Goljan, "Determining digital image origin using sensor imperfections," *Proc. SPIE*, vol. 5685, pp. 249-260, 2005.
[3] G. C. Holst, *CCD Arrays, Cameras, and Displays*, 2nd ed. JCD Publishing & SPIE Press, 1998.
[4] J. R. Janesick, *Scientific Charge-Coupled Devices*, SPIE Press, 2001.
[5] J. Tyson, "How scanners work," [Online]. Available: http://computer.howstuffworks.com/scanner.htm, 2001.
[6] M. K. Mihcak, I. Kozintsev, K. Ramchandran, and P. Moulin, "Low-complexity image denoising based on statistical modeling of wavelet coefficients," *IEEE Signal Processing Letters*, vol. 6, no. 12, pp. 300-303, 1999.
[7] C. J. C. Burges, "A tutorial on support vector machines for pattern recognition," *Data Mining and Knowledge Discovery*, vol. 2, no. 2, pp. 121-167, 1998.
[8] S. O. Jackson and J. Fuex, "Admissibility of digitally scanned images," [Online]. Available: www.iediscovery.com/news/AdmissibilityDigitalImages.pdf, 2002.
[9] A. Foi, V. Katkovnik, K. Egiazarian, and J. Astola, "Directional varying scale approximations for anisotropic signal processing," *Proc. EUSIPCO*, pp. 101-104, 2004.
[10] N. Cristianini and J. Shawe-Taylor, *An introduction to support vector machines*, Cambridge University Press, 2000.

[11] T. Joachims, “Making large-scale SVM learning practical,” *Advances in Kernel Methods - Support Vector Learning*, MIT Press, 1998.